

Smart Navigation System for Supermarket

¹Senanayake I.R., ²Weerasekara B.J.D.A., ³Siriwardana H.T.A., ⁴Ekanayake N.G.R.P., ⁵Harinda Fernando, ⁶Thamali Kelegama

^{1,2,3,4}Department of Information Technology Specializes in Information Technology, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka

^{5,6}Department of Computer System Engineering, Sri Lanka Institute of Information Technology, Malabe, Sri Lanka

Abstract - The research paper introduces the NAVRO, this is a smart navigation system that aims to ease the customer's shopping experience. This application uses machine learning algorithms and IOT based technology. This application offers a range of features to enhance the customer's shopping experience in the supermarket including real time navigation, Product localization using Lora, crowd identification and identifying raw fruits. Creation of map. Here we manually edited it in Photoshop. In this application customers can navigate to the shortest path for the product in the supermarket. The crowded area is identified in the supermarket using crowd detection features. This application shows where the relevant product is located using LoRa .This is powered by deep neural network and IOT based technology by utilizing Long Range (LoRa) communication, the proposed system seeks to improve the effectiveness and accuracy of navigation in congested areas. For reliable picture recognition and object detection, CNN and neural network techniques are used, allowing for easy product identification and localization. The system also makes use of LoRa technology to relay location data, allowing for smooth communication and accurate product tracking. Additionally, the device has mapping and crowd detection features to enhance navigation in crowded spaces. The effectiveness of the suggested system is assessed through in-depth simulations and practical trials, revealing its potential to revolutionize product management and navigation in a variety of settings. Mostly in the agriculture sector, identifying rotten fruits and vegetable has been critical. Classification of fresh and rotten fruits and vegetables is usually done by humans. But this method is ineffective. So, we proposed a method for that. From the input fruit and vegetable images, the proposed model classifies fresh and rotten. The performance of the proposed model is tested on Kaggle dataset. The findings revealed that the proposed CNN model is capable of distinguishing between fresh and rotting fruits.

Keywords: CNN, IOT, LORA, Neural network, Navigation, machine learning.

I. INTRODUCTION

Modern retail is undergoing a rapid change as cutting-edge technology is being incorporated to improve customer experiences and optimize business processes. As a vital component of the retail ecosystem, supermarkets are always looking for novel ways to enhance the effectiveness of their navigation and enhance their product management [1]. In this study, a ground-breaking Smart Navigation

System for Supermarkets with Product Identification based on LoRa (Long Range) technology is presented. It is intended to transform the shopping experience and improve the administration of supermarkets as a whole.

Challenge of navigating a large, varied supermarket can be overwhelming for customers, potentially costing businesses sales opportunities. Aisle numbering and signboards, which are common means of retail navigation, frequently fall short in terms of giving customers real-time support and individualized direction. Owners of supermarkets struggle with issues including crowd control, localization of products. These problems highlight the requirement for a smart system that smoothly combines navigation and product recognition skills.

The suggested Smart Navigation System makes use of LoRa technology, a low-power wireless communication protocol that permits long-range data transfer, in order to overcome these difficulties [2]. The system may be made scalable and affordable by including LoRa, which overcomes the drawbacks of established technologies like Bluetooth and Wi-Fi, which frequently struggle with range and scalability in expansive supermarket environments.

Providing customers with a smooth and personalized customer experience has become a key component of success in the supermarket. Customers may find it difficult to navigate large supermarkets, leading to dissatisfaction and possibly a decrease in sales. Indoor navigation procedures using Bluetooth Low Energy (BLE) beacons can provide a solution to this issue by tracking the real-time location of customers and directing them to products of interest [3].

To ensure effective staffing, queue management, and inventory control in the retail sector, especially during busy times, it is important to count the number of customers in each area of the supermarket. It is now possible to extract real-time consumer count data from CCTV developments in computer vision technology and the widespread usage of CCTV cameras in supermarkets [4]. Integrating cutting-edge solutions has become crucial to improving the shopping experience in this era of digital transformation. Our research aims to develop a system that precisely identifies and counts shoppers in various areas of the supermarket by utilizing computer vision technology and capitalizing on the pervasiveness of CCTV cameras in supermarkets. This real-time data will offer insightful information about the distribution of customers, enabling better decision-making and optimizing the use of resources during busiest shopping times.

The process of purchasing items has changed as a result of the integration of smart systems in the fast-evolving retail technology ecosystem. This study investigates the development of an advanced Smart Navigation System created especially for supermarkets. With the goal of enhancing consumer convenience and streamlining the process of purchasing goods. For the raw fruit and vegetable identification system's core function is to meticulously distinguish between fresh and rotten fruits, vegetables using cutting-edge methods in computer vision, image processing, and deep learning.

The Convolutional Neural Network (CNN) algorithm at the heart of this research was painstakingly designed to distinguish between fresh and deteriorated fruits and vegetables. Utilizing an extensive dataset compiled from Mendeley that includes 8 different fruit, vegetable categories, and the dataset includes 3200 images taken in both actual fields and fruit markets. The dataset was amplified to a sizeable 12335 images using judicious use of augmentation techniques like rotation, flipping, zooming, and shearing, which strengthened the network's robustness. The foundation of this study is the integration of state-of-the-art deep learning methods, computer vision algorithms, and image categorization methodologies.

The results of our research, as we delve into the complex mechanics of fruit quality determination, highlight the revolutionary power of intelligent systems in contemporary retail paradigms and have the potential to change supermarket navigation. The main goal of this research is to create an effective navigation system that helps customers shop more effectively by providing real-time route optimization, product localization, crowd identification and raw fruit identification.

II. LITRATURE REVIEW

Providing customers with a smooth and personalized customer experience has become a key component of success in the supermarket. Customers may find it difficult to navigate large supermarkets, leading to dissatisfaction and possibly a decrease in sales. Indoor navigation procedures using Bluetooth Low Energy (BLE) beacons [5] can provide a solution to this issue by tracking the real-time location of customers and directing them to products of interest.

An application for indoor navigation that integrates real-time location tracking and indoor navigation could be an effective solution to these issues. This application can assist customers in navigating the supermarket by presenting them with personalized options based on their location and preferences.

Many studies have investigated the use of BLE beacons for indoor navigation in a range of environments. In a survey performed by Jayakanth Kunhoth, AbdelGhani Karkar, Somaya AlMaadeed & Abdulla Al-Ali for instance [6], BLE beacons were utilized to direct shoppers in a supermarket. Customers were able to navigate the mall more simply, and the deployment of BLE beacons reduced the amount of time shoppers spent in the mall, according to the study. The study also highlighted the potential for BLE beacons to boost sales by reducing the time shoppers spend in the supermarket.

Likewise, investigated the use of BLE beacons for indoor navigation in a museum. The study indicated that the introduction of BLE beacons enhanced the tourist experience and increased the likelihood that museum visitors would view every exhibit. The study also found that BLE beacons have the ability to increase visitor engagement and satisfaction.

The Internet of Things' (IoT) explosive growth has created new possibilities for improving the operational effectiveness and consumer experience in retail settings, among other factors. In order to bridge the gap between the offline and online purchasing experiences, indoor placement and localization have become crucial elements. For its applicability in delivering dependable and long-range communication for IoT applications, including indoor location in complicated situations like supermarkets, LoRa (Long Range) technology has attracted interest recently [7]. It has been investigated to use Wi-Fi, Bluetooth, RFID, and Ultra-Wideband (UWB) as indoor localization methods. However, each method has its own set of drawbacks, including those related to accuracy, price, and energy use. A possible alternative for indoor positioning is LoRa [8], which is well known for its low power consumption, long communication range, and flexibility to different situations. Due to its capacity to pass through barriers and sustain communication over great

distances, LoRa technology, which was first created for long-range communication in outdoor settings [9], has been modified for indoor localization. To increase accuracy, machine learning techniques have been deeply incorporated into indoor positioning systems. Particularly deep neural networks have demonstrated potential in extracting complicated patterns from signal data. In conclusion, the incorporation of LoRa technology in indoor localization offers a potentially fruitful way to improve customer experiences and streamline business processes in supermarkets. Previous studies have shown that LoRa's long-range communication and versatility make it an appropriate contender for precise and affordable indoor positioning.

The adoption of modern technologies has significantly changed the retail industry. Many studies have investigated the use of computer vision in numerous fields, such as crowd counting and identification. Researchers have shown that CCTV cameras can be used to collect real-time information on customer counts and movement patterns inside supermarkets. The literature currently in print emphasizes the value of precise crowd identification for improving staffing levels, streamlining line operations, and ensuring effective inventory management. Additionally, improvements in machine learning algorithms have made it possible for more accurate and reliable crowd counting techniques, increasing the viability of implementing such systems in challenging retail environments. Various methods for crowd identification and counting, such as object detection, tracking, and density estimation, have been studied in earlier research. Studies have also looked into using AI-driven tools to distinguish between customers and employees, giving them more specific information about crowd dynamics. These breakthroughs highlight the potential advantages of our suggested Smart Navigation System, which seeks to expand upon and contribute to the body of knowledge by offering a comprehensive solution suited to the particular difficulties faced by the retail industry. The development of computer vision algorithms [10] for crowd analysis and real-time consumer counts in supermarkets has been the subject of numerous studies.

In the context of retail and consumer-focused technologies, the field of computer vision and image processing has made notable strides. The need of precise fruit quality assessment in supermarket settings has been highlighted by earlier research. Convolutional Neural Networks (CNNs) have been shown to be effective for image classification tasks in numerous studies, showing that they can discern between a variety of objects and materials. In addition, the use of deep learning techniques in grocery store environments has drawn interest, with uses that span inventory control to product recognition. These technologies have the

potential to improve supply chains and streamline consumer interactions.

The use of computer vision to distinguish between fresh and decaying fruit has produced useful insights in the fields of agriculture and horticulture. The number and diversity of datasets have been increased via augmentation approaches, which has improved the resilience and generalizability of models. While the potential of image-based quality assessment is highlighted in prior literature, the suggested Smart Navigation System for supermarkets represents a considerable advancement. This research pioneers a comprehensive solution to smoothly lead customers through the store while assuring the freshness of their chosen fruits by combining the strengths of CNNs, image processing, and deep learning. This study pushes the boundaries of retail technology by providing a creative and useful solution to improve grocery shopping experience and demonstrate the revolutionary power of intelligent systems.

III. METHODOLOGY

The methodology describes strategy and methods used for smart navigation system. This system enable customers to easily navigate through the supermarket, identify products easily, and identify raw fruits and to detect the crowd in the supermarket. This system will ease the shopping experience for customers. For creating this system used machine learning algorithms and IOT based technology.

A) Real time navigation

An application for indoor navigation that integrates real-time location tracking and indoor navigation could be an effective solution to these issues. This application can assist customers in navigating the supermarket by presenting them with personalized options based on their location and preferences. Many studies have investigated the use of BLE beacons for indoor navigation in a range of environments. Customers were able to navigate the mall more simply, and the deployment of BLE beacons reduced the amount of time shoppers spent in the mall, according to the study. The study also highlighted the potential for BLE beacons to boost sales by reducing the time shoppers spend in the supermarket. The challenges of customer navigation in large supermarkets and to improve their experience through the utilization of Bluetooth Low Energy (BLE) beacons. In response to the growing importance of personalized experiences in retail, this research aims to develop an indoor navigation application that integrates real-time location tracking and personalized recommendations based on customer preferences, leveraging BLE beacons and advanced technologies. By enhancing location accuracy, offering real-time product information, tailoring recommendations to individual preferences, and

optimizing path planning, the proposed indoor navigation application aims to elevate overall customer experiences. Validation procedures, including user surveys, provide insights into the practical utility of the application and its potential to positively reshape supermarket navigation experiences.

In the figure 1 path finding for the product in the door navigation initialize the map to the model is shown.

```
[ ] # the latitude and Longitude coordinates
UMMlocation = (49.49216583285166, 8.484229445457458)
map_UMM = folium.Map(location = UMMlocation, width = "75%", zoom_start = 17)
map_UMM
```

Figure 1

Afterwards, in the figure 2 and 3 shows retrieve the route between the user's location and the product by utilizing the coordinates in the Geojson map. Extract the geometry coordinates and present the finalized path as a preview.

```
[ ] testGeoJson = 'SuperMarketNavigator/GeoResources/path/w17.geojson'

[ ] def switchPosition(coordinate):
    temp = coordinate[0]
    coordinate[0] = coordinate[1]
    coordinate[1] = temp
    return coordinate

[ ] with open(testGeoJson) as f:
    testWay = json.load(f)

    for feature in testWay['features']:
        path = feature['geometry']['coordinates']
        finalPath = list(map(switchPosition,path))
        finalPath

[ ] path = 'SuperMarketNavigator/GeoResources/path/w17.geojson'
folium.plugins.AntPath([[49.49213534374249, 8.484166413545609],
[49.492327860377041, 8.484299182891846],
[49.49233047371309, 8.484493643045425],
[49.492218099851804, 8.484871834516525],
[49.49142363542676, 8.48755384635925],
[49.49185222967887, 8.487834334373474],
[49.491712849846946, 8.488343954086304],
[49.492029938390125, 8.488638997077942],
[49.49251776290861, 8.488982319831848],
[49.49222506878094, 8.489341735839844],
[49.49217977072303, 8.489529490470806],
[49.49220764645021, 8.489856719970703]]).add_to(map_UMM)
map_UMM
```

Figure 2

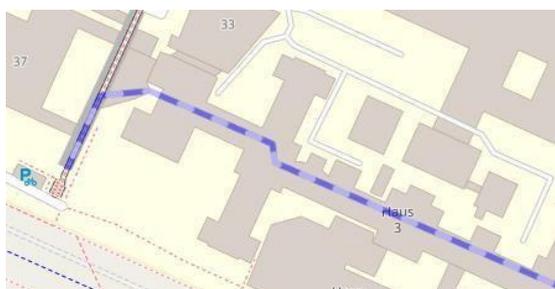


Figure 3

B) Product localization using Lora tags

For the proposed system the data collection is done using Lora based IOT devices and get the RSSI values and create the

dataset. From using created dataset train the model. The main objective is identifying products using Lora on the products makes it simple for customers to find products. When a customer's smartphone detects signals from Lora attached to products, the navigation system can direct them to the product's location within the supermarket. For this component put Lora tags in the supermarket and also attach some Lora tags to products. From the Lora tags only coming the signal strengths. To predict the location need some Lora tags more than three.

```
def localization_model():
    model = tf.keras.models.Sequential()
    model.add(tf.keras.layers.Dense(50, input_dim=train_x.shape[1], activation='sigmoid'))
    model.add(tf.keras.layers.BatchNormalization())
    model.add(tf.keras.layers.Dense(50, activation='relu'))
    model.add(tf.keras.layers.Dense(50, activation='relu'))
    model.add(tf.keras.layers.Dense(2, activation='relu'))
    # compile model
    model.compile(
        loss='mse',
        optimizer=tf.keras.optimizers.Adam(.001),
        metrics=['mae']
    )
    return model
```

Figure 4: Model Implementation

Deployed the Lora tags and connected to the Firebase. To predict the location training a machine learning model using deep neural network. Then get all the RSSI values from the Lora tags to the each product and send it to the database. After receiving RSSI values to the database from the machine learning model the location is predicted using x, y coordinates. The x, y coordinates are coming as longitude and latitude.

```
# Plot training & validation loss and mae values

plt.plot(hist.history['loss'])
plt.plot(hist.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper right')
plt.show()

plt.plot(hist.history['mae'])
plt.plot(hist.history['val_mae'])
plt.title('Model mae')
plt.ylabel('mae')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper right')
plt.show()
```

Figure 5: Plot Training and validation loss

From the machine learning model it gives the location that we want from the exact product. The six devices signal strengths by default set it to the database. The six devices means Lora tags. From the Lora tags it will send signals to the product. From the product it will get the signal strength from all the devices.

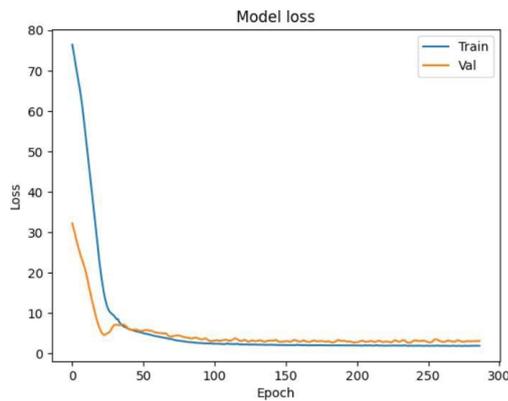


Figure 6: Model Loss Graph

The predicted location will send to the mobile app and the mobile app shows the exact location of the product to the customer.

C) Rotten Fruit and Vegetable Identification

3200 photos of both fresh and rotten apples were collected from various fruit stands and orchards to create a diversified dataset. Rotation, flipping, zooming, and shearing were among the augmentation methods used to create a dataset with 12335 more photos. The robustness and generalization ability of the model were significantly improved by the addition of this dataset [11]. The photos underwent preprocessing by being resized to a consistent dimension, having pixel values normalized, and being converted into formats appropriate for deep learning. To give the neural network meaningful input, relevant features have to be extracted from the photos. [12]

For the purpose of extracting hierarchical features, a CNN architecture with multiple convolutional and pooling layers was developed. Convolutional, activation, pooling, and fully connected layers made up the model's architecture, which culminated in a SoftMax layer for classification. [13]

The training, validation, and testing sets were created from the augmented dataset. The validation set helped with hyper parameter tuning while the training set was used to train the CNN model. On the testing set, performance evaluation was done using metrics like accuracy, precision, recall, and F1-score. [14] The trained CNN model was included into the supermarket's Smart Navigation System, allowing for real-time fruit and vegetable rot detection. User testing and comparison with manual quality evaluation were used to verify the system's efficacy. [15]

This system uses visual data to identify rotting fruits and vegetables using a CNN-based model. Heat maps and color shifts are used by the model to detect objects. After being

trained on a dataset, the system distinguishes and highlights fruit rotting with an accuracy of 0.93.

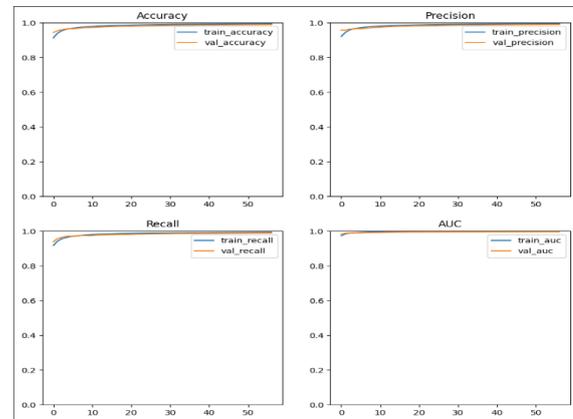


Figure 7: Accuracy graph

A neural network model for rotting fruit, vegetable detection is defined in this code. With more layers, Exception serves as the foundation of the architecture. Global pooling and dropout are the steps that come after dense layers for feature extraction. The concept is intended to divide photos into categories that are either rotten or not. The summary offers details about its composition, facilitating model comprehension.

```
def rotten_detector():
    functional_model = tf.keras.applications.Xception(
        weights="imagenet",
        include_top=False
    )
    functional_model.trainable = True
    inputs = tf.keras.Input(shape=input_shape)
    x = functional_model(inputs, training=True)
    x = tf.keras.layers.GlobalAveragePooling2D()(x)
    x = tf.keras.layers.Dropout(0.2)(x)
    x = tf.keras.layers.Dense(512, activation='relu')(x)
    x = tf.keras.layers.Dropout(0.2)(x)
    x = tf.keras.layers.Dense(256, activation='relu')(x)
    x = tf.keras.layers.Dropout(0.2)(x)
    outputs = tf.keras.layers.Dense(1, activation='sigmoid')(x)
    model = tf.keras.Model(inputs=inputs, outputs=outputs)
    model.summary()
    return model
```

Figure 8: Model Implementation

D) Crowd Identification using CCTV

Using CCTV footage and Firebase, a real-time crowd analysis and consumer counting system is being developed for indoor supermarket navigation. Firstly, hardware setup is necessary to install high-resolution CCTV cameras at strategic positions in the supermarket to gather footage of consumers entering and exiting the store. In order to train and evaluate the computer vision system, a collection of CCTV footage must be gathered and annotated. To reliably recognize customers in the supermarket, monitor their movement, and count them, the computer vision system must be designed and trained using open-source computer vision libraries like OpenCV and TensorFlow. Thirdly, to locate congested regions in the supermarket, a density-based clustering algorithm and a

graph-based analysis algorithm should be created and put into use. In order to train and evaluate the computer vision system, a collection of CCTV footage must be gathered and annotated. To reliably recognize customers in the supermarket, monitor their movement, and count them, the computer vision system must be designed and trained using open-source computer vision libraries like OpenCV and TensorFlow. Thirdly, to locate congested regions in the supermarket, a density-based clustering algorithm and a graph-based analysis algorithm should be created and put into use. In order to train and evaluate the computer vision system, a collection of CCTV footage must be gathered and annotated. To reliably recognized customers in the supermarket, monitor their movement, and count them, the computer vision system must be designed and trained using open-source computer vision libraries like OpenCV and TensorFlow. Thirdly, to locate congested regions in the supermarket, a density-based clustering algorithm and a graph-based analysis algorithm should be created and put into use. Fifth, in order to display the real-time customer count data and congested area data, a graphical user interface needs to be constructed utilizing web development technologies including HTML, CSS, and JavaScript. Ultimately, it is necessary to construct an interior supermarket navigation system utilizing web development techniques and combine customer count and crowded area data from the Firebase database. The system should be assessed for accuracy and efficiency, and user guides and technical documentation should be given for the software design, implementation, and testing.

The CNN model's loss value decreases after training and validation, indicating improved accuracy. This suggests that the model's predictive performance enhances as it learns from the data. Lower loss values signify better alignment between predictions and actual outcomes, demonstrating the model's learning effectiveness.

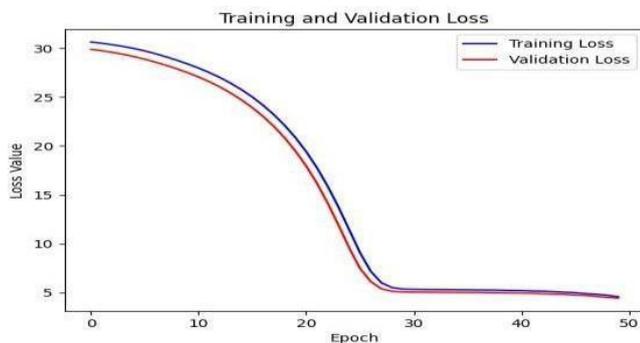


Figure 9: Training and Validation loss graph

Below code reads the "labels.csv" CSV file from the "data/crowd-counting" directory. The columns are given new names, "id" and "people," which stand for image IDs and

associated people counts. For easy review, the Data Frame's first few rows are shown via the. Head() function.

```
label_df = pd.read_csv('data/crowd-counting/labels.csv')
label_df.columns = ['id', 'people']
label_df.head()
```

	id	people
0	1	35
1	2	41
2	3	41
3	4	44
4	5	41

Figure 10: Customer count

IV. CONCLUSION AND FUTURE WORKS

The development of the smart navigation system offers the customers to easy and efficient shopping experience in the supermarket. This system helps customers to easily navigate through the supermarket, products localization, crowd identification and raw fruits recognition. Our solution offers a seamless and effective shopping experience by addressing the issues experienced by customers in large supermarkets. We have demonstrated the viability of improving navigation, exact product positioning, crowd identification, and the identification of raw fruits in real time by utilizing modern technologies.

When shopping in a large supermarket, customers frequently face the difficult task of navigating through confusing aisles, pinpointing the precise location of desired products, navigating traffic during peak hours, and determining the quality of declarable goods, particularly raw fruits and vegetables. Our navigation technology thoughtfully addresses these complex problems, delivering a stress-free and successful shopping experience. This technological convergence opens up a whole new world of retail possibilities and is poised to completely change how customers interact with supermarket settings.

The actual findings from our thorough testing clearly show how effective our suggested approach is at improving the entire shopping experience. Now that customers have a clear and accurate navigation, they can easily navigate throughout the supermarket. Our system's accurate product localization, made possible by Lora technology, is one of its major components. Through real-time tracking and locating, shoppers can now quickly find their preferred items, even in large supermarkets. As a result, there is no longer a need for searching for the products in the supermarket. Decreasing the time and effort needed to find products at the supermarket. The Lora tag placement and signal strength, the system may be made more accurate and efficient while also increasing

identifying the products in the supermarket. When customer is searching for fruits and vegetables system will show the raw fruits, raw vegetables and customer can easily get the healthy and ripe fruits. This reduces frustration and boosts productivity. Our method gives users the knowledge they need to choose raw fruits wisely, which is important for consumers who are concerned about their health. They get immediate information about the fruit's quality, freshness, and nutritional worth, which helps them make better decisions and have an overall better buying experience.

Our research potential future applications are very promising. The algorithms for identifying crowds can be improved as we learn more about artificial intelligence and machine learning, increasing their precision and effectiveness. In turn, this will help regulate crowd flow more effectively, ensuring that customers can move through the store easily even during busy times. Our system will become even more adaptable by extending our product localization capabilities to include a wider range of commodities, satisfying different shopping requirements. The system's user interface and overall performance will need to be improved in order to make it even more user- friendly and efficient, therefore collecting and implementing user feedback will be essential. The power of real-time navigation, LoRa-based product localization, crowd recognition, and fresh fruit assessment in supermarkets are combined in our research to create a paradigm-shifting idea. This convergence of technology provides a significant response to consumers' concerns, opening the path for a shopping experience that is both effective and enjoyable. We have the capacity to transform the future of retail by utilizing modern technology and consistently improving our strategy, making it more practical, wholesome, and gratifying for consumers around the world.

REFERENCES

- [1] S. P. S. S. P. R. R. Shreya Kothavale, "ieeexplore," 10 January 2022. [Online]. Available: <https://ieeexplore.ieee.org/document/9670948>.
- [2] L. E. Marquez and M. Calle, 24 February 2023. [Online]. Available: <https://ieeexplore.ieee.org/document/10052669>.
- [3] S. Patil, December 2016. [Online]. Available: https://www.researchgate.net/publication/316613991_Indoor_Positioning_System_using_Bluetooth_Low_Energy.
- [4] V. Nogueira. [Online]. Available: <https://ieeexplore.ieee.org/document/8919725>.
- [5] G. C. a. O. S. P. Dickinson, 17 November 2016. [Online]. Available: <https://ieeexplore.ieee.org/document/7743684>.
- [6] K. P. a. M. Chamchoy, March 2020. [Online]. Available: <https://ieeexplore.ieee.org/document/9090691>.
- [7] K.-H. Lam and C.-C. Cheung, 09 September 2019. [Online]. Available: <https://ieeexplore.ieee.org/document/8827665>.
- [8] W.-T. Sung, S.-J. Hsiao, S.-Y. Wang and Jen- Hsiang Chou, 28 November 2019. [Online]. Available: <https://ieeexplore.ieee.org/document/8915>.
- [9] K.-H. Lam, C.-C. Cheung and Wah-Ching Lee, 23 November 2017. [Online]. Available: <https://ieeexplore.ieee.org/document/8115843>.
- [10] K. Rohit, March 2017. [Online]. Available: <https://ieeexplore.ieee.org/document/8275999>.
- [11] "Data augmentation for improving deep learning in image classification problem," May 2018. [Online]. Available: https://www.researchgate.net/publication/325920702_Data_augmentation_for_improving_deep_learning_in_image_classification_problem.
- [12] C. Gonzalez, "Digital Image Processing," [Online]. Available: <https://dl.icdst.org/pdfs/files4/01c56e081202b62bd7d3b4f8545775fb.pdf>.
- [13] E. Duryea, "Scientific Research," November 2016. [Online]. Available: [https://www.scirp.org/\(S\(i43dyn45teexjx455qlt3d2q\)\)/reference/referencespapers.aspx?referenceid=1911084&utm_campaign=17209361273&utm_source=lixiaofang&utm_medium=adwords&utm_term=&utm_content=_c&gad=1&gclid=Cj0KCCQjwoeemBhCfARIsADR2QCs4L3rFEe2VsrP7eoIvIy](https://www.scirp.org/(S(i43dyn45teexjx455qlt3d2q))/reference/referencespapers.aspx?referenceid=1911084&utm_campaign=17209361273&utm_source=lixiaofang&utm_medium=adwords&utm_term=&utm_content=_c&gad=1&gclid=Cj0KCCQjwoeemBhCfARIsADR2QCs4L3rFEe2VsrP7eoIvIy).
- [14] X. Zhang, "Deep Residual Learning for Image Recognition," 2016. [Online]. Available: <https://ieeexplore.ieee.org/document/7780459>.
- [15] W. Fang, "Real-time Object Detection of Retail Products for Eye Tracking," 2020. [Online]. Available: https://www.researchgate.net/publication/353096934_Realtime_Object_Detection_of_Retal_Products_for_Eye_Tracking.

Citation of this Article:

Senanayake I.R, Weerasekara B.J.D.A, Siriwardana H.T.A, Ekanayake N.G.R.P, Harinda Fernando, Thamali Kelegama, "Smart Navigation System for Supermarket" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 10, pp 543-550, October 2023. Article DOI <https://doi.org/10.47001/IRJIET/2023.710071>
